A Roadmap Towards Intelligent and Autonomous Object Manipulation for Assembly Tasks

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I. Undervalued Complexity of Object Placing

Despite the large scientific interest on robot learning for object picking tasks [1]–[4], the research on object placing is too limited. Commonly, placing is simplistically considered as a trivial task, but real life manipulation problems indicate the exact opposite. A placing task can have different levels of complexity, ranging from the simplest tabletop placing of an object, to more complex cases such as loading a dishwasher and assembling industrial parts. In this paper we argue that *assembly can and needs to be seen as a complex placing task*. Thus, the need for systems with advanced placing capabilities becomes evident.

We consider machine learning algorithms, as a potential approach for dealing with the different variants of the placing task and introducing autonomy to the robotic system. Thus, exploiting the capability of machine learning algorithms for knowledge generalization, a generic approach could be developed for dealing with the wide range of object placing problems. Also the robotic system can be considered as autonomous since re-programming between small variants of a placing task may not be required. As a result, the manipulator could be able to adapt to a variety of environments and perform a placing task independently of the manipulated object or the placement location.

There exists prior work that applies machine learning techniques to find suitable placing locations in cluttered environments [5], [6] or learn a low cost manipulator to place and stack objects [7]. Furthermore, ways of compensating for uncertainties that arise due to the interaction with physical objects or imperfect sensors within a robotic assembly scenario have also been considered in [8].

However, the described approaches focus on only one of the two modules that are needed for developing a complete intelligent and autonomous object placing robotic manipulator. The work in progress, described in this paper, aims to provide the framework and a broad description of a robotic manipulation system that bridges the gap between those two modules, namely the cognition and the control one. Furthermore, we plan to implement those modules using machine learning algorithms. This would affect the manipulator's capability to deal with a larger variety of object placing tasks and objects to be manipulated.

II. Description of a Robotic Manipulation System

In this section we will describe the main parts of a robotic manipulator system, that is the cognition and the control modules, as shown in Fig. 1. Also, we will discuss possible machine learning algorithms that could be used to implement such an adaptive system, together with the rationale behind their selection.

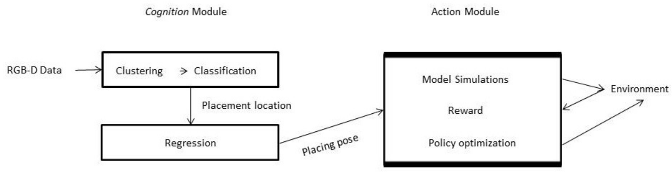

Fig. 1. Block diagram of an adaptive robotic manipulation system

A. Cognition Module

The cognition module of a placing task, is mainly responsible for sensing and anticipating the environment. This involves three main functionalities: (1) obstacle localization; (2) derivation of placement location; and (3) derivation of object's placing pose. At the first step, a segmentation process will be applied to a captured point cloud. The segmented point-cloud clusters will then be classified as potential placement locations or obstacles.

The above described process can be implemented using both one unsupervised and one supervised learning algorithm. The first will create the point cloud clusters, and the second will classify the generated clusters. The classifier's training set, will consist of geometric features extracted from the point clouds of various locations. Such locations, could be tables, pallets, boxes, e.t.c. Each instance of the training set will be labelled as suitable or not suitable for placement. Thus, this corresponds to a binary classification problem.

After the derivation of the placement location, a suitable placing pose will be derived from the cognition module. The inputs will be geometric features extracted from both the placement location and the manipulated objects. The outputs will be continuous and represent the object's placing pose. Thus, this process corresponds to a regression problem. The training set will consist of suitable placing poses of various objects on different placement locations. Both the derived placement locations and the object's placing pose will be fed in the control module, which is responsible for the emergence of the suitable manipulator's movement.

B. Control Module

The goal of the control module is to learn the parameters of the controller, in order to place the object on a certain placement location and with a certain placing pose, as derived from the cognition module. We plan to address this problem using a model-based reinforcement learning algorithm.

We choose a model-based method instead of a model-free because it requires less interactions with the environment and the learning time can be significantly less. This method requires a good model of the manipulator's transition dynamics. The model will generate the probability of reaching a state given the current state and the applied motor commands.

Another significant characteristic of the reinforcement learning algorithm is the definition of a reward function. The reward will be a function of the manipulated object's state, its final desired state and the obstacles' location. The reward function will be used for the derivation of an optimized policy. The policy search problem corresponds to finding the parameters of a policy (controller) that maximizes the expected long-term reward. This problem will be addressed by employing a policy gradient-based approach. Finally, the control module should be able to predict the manipulator's trajectory in the long run. This is needed for the derivation of the long-term reward. The long-term trajectory predictions will be generated by sampling trajectories from the model.

III. Roadmap Towards Assembly

The described system will be applied on object placing problems of increasing complexity. The first test case will be palletizing of boxes. This task requires objects to be placed in such a away that they will fit the pallet. Also, their positioning should be stable in order to avoid damage of humans or objects. This test-case will provide feed-back about the system's ability to place a large amount of objects on a defined placement location and avoid obstacles.

The second test case will be kitting of objects. Objects have to be placed inside a kit which is divided by compartments. The objects should be placed in a certain position and with specific orientation in order to fit the compartments. The robotic manipulation system should be able to match each of the manipulated objects with the correct compartment (placement location) and also provide the correct placing pose.

One of the most challenging industrial tasks that involves objects placing is robotic assembly of parts. It requires both a suitable cognition and control module for achieving a successful implementation. The function of the cognition module is similar as with the kitting task, since it matches parts with placement locations which could be holes or compartments. Additionally, the control module, should be capable of providing the required motor commands for driving the part to the desired position and with the appropriate orientation. It should also be able to provide coordination between sensors and motors in order to stably join two parts.

IV. Conclusion

This paper presented a roadmap towards exploiting robot learning for object placing tasks. The described robotic manipulation system will employ machine learning algorithms for both inferring suitable placement locations and object placing poses. Furthermore, it will be capable of generating the required motor commands for achieving a suitable collision-free movement.

In order to achieve the goal of intelligent autonomous assembly, the robotic manipulator system will be applied on test-cases of increasing complexity, namely palletizing and kitting. Those test cases, will provide feed-back about the necessary modifications of the system, that will ultimately make it capable of performing assembly tasks autonomously.

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References

[1] A. Saxena, J. Driemeyer, and A. Y. Ng, "Robotic grasping of novel objects using vision," *The International Journal of Robotics Research*, vol. 27, no. 2, pp. 157–173, 2008.

[2] O. Kroemer, R. Detry, J. Piater, and J. Peters, "Combining active learning and reactive control for robot grasping," *Robotics and Autonomous Systems*, vol. 58, no. 9, pp. 1105–1116, 2010.

[3] I. Lenz, H. Lee, and A. Saxena, "Deep learning for detecting robotic grasps," in *Robotics: Science & Systems (RSS)*, 2013.

[4] R. Pelossof, A. Miller, P. Allen, and T. Jebara, "An SVM learning approach to robotic grasping," in *Robotics and Automation, 2004. Proceedings. ICRA'04. 2004 IEEE International Conference*, vol. 4. IEEE, 2004, pp. 3512–3518.

[5] M. Schuster, J. Okerman, H. Nguyen, J. Rehg, and C. Kemp, "Perceiving clutter and surfaces for object placement in indoor environments," in *Humanoid Robots (Humanoids), 2010 10th IEEE-RAS International Conference*, 2010, pp. 152–159.

[6] Y. Jiang, M. Lim, C. Zheng, and A. Saxena, "Learning to place new objects in a scene," *The International Journal of Robotics Research*, vol. 31, no. 9, pp. 1021–1043, 2012.

[7] M. P. Deisenroth, C. E. Rasmussen, and D. Fox, "Learning to control a low-cost manipulator using data-efficient reinforcement learning," in *Robotics: Science & Systems (RSS)*, 2011.

[8] A. Stolt, M. Linderoth, A. Robertsson, and R. Johansson, "Force controlled robotic assembly without a force sensor," in *Robotics and Automation (ICRA), 2012 IEEE International Conference on*. IEEE, 2012, pp. 1538–1543.